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Marketer's Guide to the Algorithm

Using Machine Learning to Enhance Marketing

Bachelor's Thesis
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Abstract

In the last few years machine learning, a subset of artificial intelligence (AI), has become widely available and relatively effective at solving many business problems. This thesis reviews top marketing journal papers over the period 2012–2019 on the use of machine learning, offers a state-of-the-art overview on what is currently known about this quickly evolving field, and identifies avenues for further research. The review has three major findings: 1) Machine learning techniques show a significant improvement over traditional methods in most cases. 2) Machine learning has become a mainstream tool for researchers and practitioners in structuring very large amounts of user-generated content for marketing insights. 3) Despite the promising results, most uses of the technology have been researched relatively little in marketing literature. There exist several major research gaps, especially in prediction, personalization, segmentation and customer experience. Directions for further research indicate a pressing need for more research in this important area. Theoretical and managerial implications are provided.

Keywords Systematic review; machine learning; artificial intelligence; topic model; latent Dirichlet allocation; sentiment analysis; user-generated content; prediction; marketing insights

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1. Introduction

"It seems probable that once the machine thinking method had started, it would not take long to outstrip our feeble powers… They would be able to converse with each other to sharpen their wits. At some stage therefore, we should have to expect the machines to take control."
— *Alan Turing*

Artificial Intelligence (AI), and especially its major branch, machine learning, have the potential to be the most important general-purpose technologies of our era, due to the ability to automate repetitive tasks and achieve superhuman performance in a wide range of activities (Brynjolfsson & McAfee 2017). In 2016, tech companies and startups invested between 26 and 39 billion dollars in AI, a three-time external investment growth from 2013. Of this sum, 60 % was invested in machine learning (Bughin et al. 2017). This is not the first time AI is thought to change the business landscape and there are sceptics and uncertainty (e.g. Piekniewski 2018; Bughin et al. 2017). Others, such as top consulting firm McKinsey, argue that it is unlikely we are experiencing a phase in a boom-and-bust cycle and that according to their analysis, AI is starting to deliver real-life business benefits, with early adopters having higher profit margins (Bughin et al. 2017).

In the field of marketing, the possibilities offered by machine learning have created a lot of enthusiasm. In addition to automating repetitive tasks and analyzing big data, machine learning offers the promise of more evidence-based decision-making (Jordan & Mitchell, 2015). Marketers expect AI to provide most of the growth over the next two years (Olson & Levy 2018), and according to a 2016 survey, over 50% of CMOs estimate that AI will impact marketing more than social media ever has (Weber Shandwick 2016). In the editorial for Marketing Science's special issue on big data, Chintagunta et al. (2016) urge marketers to embrace machine learning in order to take advantage of the extremely large, real-time data now available. Machine learning is expected to make marketers more efficient through automation, offer scalable marketing personalization, create deeper relationships through marketing insights, optimize marketing-mix spending, deliver what customers want when they want it, create more robust sales predictions and increase marketing ROI (Wedel & Kannan 2016; Conick 2016; Olson & Levy 2018). What's more, modern machine learning tools are no longer restricted to IT specialists.

Despite this, it seems that marketing academia have not yet fully embraced this new world. Machine learning methods are popular among practitioners but have been addressed relatively seldom in marketing literature (Wedel & Kannan 2016). For example, the Marketing Science Institute is currently calling for research in many machine learning and AI-related areas, such as machine learning best practices, marketing personalization, human/tech interfaces and programmatic real-time campaigns (MSI 2018).

Although there is wide interest in the topic, there is no up-to-date review of research on the application of machine learning in marketing. Previously, Martínez-López and Casillas (2013) have conducted a literature review of AI systems in industrial marketing, but the review is six years old and it is important to periodically review this quickly evolving field. More recently, Wedel and Kannan (2016) have examined marketing analytics methods and trends, including machine learning from a narrower scope, and Balducci and Marinova (2018) have reviewed articles using machine learning methods from an unstructured data viewpoint. Others, such as Lamberton and Stephen's (2016) review on digital marketing, social media and mobile marketing, do not mention machine learning or review other methodological work, although they do discuss machine learning-powered applications, such as recommendation systems.

This paper aims to fill this gap and expand current marketing literature accordingly. This systematic review offers an overview on what is currently known about machine learning approaches in marketing. According to Palmatier et al. (2018), such review papers act as an important and required part of science by integrating and synthesizing research and offering a state-of-the-art snapshot of an area of interest (Bem 1995). Although non-meta-analytic reviews are relatively rare in marketing, they are often widely cited when published (Bettencourt & Houston 2001). The need for such reviews is highlighted also by the editorial initiative by the Journal of the Academy of Marketing Science, which focuses on expanding the amount of review articles in marketing (Palmatier et al. 2018).

Based on the guidelines laid out by Palmatier et al. (2018), this thesis contributes to existing literature in two ways: 1) by providing an up-to-date synthesis of the current knowledge of machine learning in marketing, and 2) by describing future research directions. I will employ a descriptive approach, with the following research problem: What are the major research gaps regarding machine learning in current marketing literature? My specific research questions are:

1) To what extent are machine learning techniques addressed in research published in top marketing journals in 2012-2019?

2) According to published papers and calls for research, what application areas of machine learning are understudied in marketing literature at the moment?

This thesis is structured in the following way. First, I will define the most important terms. Second, I will review existing literature in detail. I will note the number of machine-learning-related articles in leading marketing journals and categorize the research into relevant topic areas. Third, I will interpret and discuss the findings and implications of my research by compiling calls for research from notable sources as well as some of the articles reviewed. Finally, I will conclude the research and discuss the limitations of this paper.

2. Definitions

2.1 Artificial Intelligence

Artificial intelligence (AI) can be described as the ability of a machine to mimic human intelligence, including tasks like reasoning, planning, perception and language understanding (Conick 2016). Many of the AI applications do not include actual intelligence, instead displaying human-like accuracy, such as computer vision. Other examples of AI technology are robotics, autonomous vehicles, virtual agents and machine learning (Chui et al. 2018). AI covers many techniques and applications, and there is no broadly accepted definition. All of the technologies in this paper are considered "weak AI", which perform a narrow task, instead of a general artificial intelligence, which has not been developed yet (Bughin et al. 2017).

2.2 Machine learning

Machine learning is at the heart of artificial intelligence, providing computers with the capability to improve by themselves, through experience (Jordan & Mitchell 2015). A machine learning system is able to learn new things from examples, without humans explicitly programming it (Conick 2016). Machine learning algorithms are trained with data and used to replace a less cost-effective manual programming process. With enough training data machine learning systems can usually surpass humans in the task at hand (Brynjolfsson & Mitchell 2018). Machine learning makes it possible to create practical AI software applications for computer vision, speech recognition, robotics and natural language processing (Jordan & Mitchell, 2015). Popular algorithms include linear regression, logistic regression, linear/quadratic discriminant analysis, support vector machines, k-nearest neighbor and neural networks (Chui et al. 2018).

Machine learning techniques can be categorized as supervised learning, unsupervised learning and reinforcement learning (Chui et al. 2018b). In supervised learning humans are needed to label all of the training data, including both the input and the output. Most of the machine learning models today are trained this way. In unsupervised learning, the data is not labeled, and it is up to the algorithm to create groups. Reinforcement learning algorithms learn by trial and error (Chui et al. 2018b). Nearly all of the current progress in AI can be attributed to supervised machine learning, especially deep learning algorithms (Ng 2016).

Machine learning algorithms perform very well in certain confined areas, whereas they are ineffective in others (Brynjolfsson & Mitchell 2018). Machine learning is good at for example classifying images, labelling text and prediction. The algorithms work well with large amounts of training data and when goals are clearly described, even if the best process to reach these goals is not known. Machine learning is good with statistical correlation, but not yet good at causal effects and common sense (Brynjolfsson & Mitchell 2018).

2.3 Deep Learning

Deep learning is a subset of machine learning. The most exciting developments in supervised machine learning are due to deep neural networks, which are loosely based on the human brain (Ng 2016). In deep learning, layers of "neurons" form a network that processes the input data and learns increasingly complex features of the data at each layer (Chui et al. 2018). The most frequently used ones are convolutional and recurrent networks (Chui et al. 2018b).

The deep learning layers form a black box, which make it hard for humans to understand why a certain decision was reached. Nascent techniques, such as local interpretable model-agnostic explanations, generalized additive models and attention techniques may help to demystify how deep learning reaches its conclusions and will likely make the adoption of these techniques much faster (Chui et al. 2018b).

2.4 Topic Modeling

The ability to understand and categorize language is of special interest to many marketing practitioners and researchers, as evidenced by this review. Topic modeling is a natural language processing application using unsupervised learning (Jordan & Mitchell, 2015), although it can be extended to supervised learning as well (Blei & McAuliffe 2010). In topic modeling, written data is usually analyzed as a "bag of words", which are grouped according to underlying semantic topics, based on probability distributions. This allows marketers to understand the semantic structure of large sets of data, such as reviews and tweets, and find patterns and themes (Blei & McAuliffe 2010). The most popular topic modeling technique is the latent Dirichlet allocation (LDA) created by Blei et al. (2003). LDA can be used for large amounts of data (Mimno et al. 2012) and is well suited to analyzing data that contains multiple, intermingled topics (Dyer et al. 2017).

3. Machine Learning in Marketing Literature

In this section I will review the current academic literature on using machine learning in marketing. According to the steps laid out by Palmatier et al. (2018), I identify relevant studies by defining the sampling unit to be any use of machine learning techniques in academic marketing journal papers. The data is extracted to standardized templates, in this case tables containing the topic areas and summaries of research (in appendix 1), as well as a more detailed table for the ten most cited articles (table 3). The journals and the respective number of articles appearing in the review are shown in table 1.

Journal	**# of Articles**	**SJR**
Journal of Marketing	5	8.616
Journal of Marketing Research	7	7.819
Marketing Science	22	7.580
Journal of Consumer Research	1	5.856
Journal of the Academy of Marketing Science	2	4.614
Journal of Interactive Marketing	1	3.400
International Journal of Research in Marketing	2	2.528
Journal of Advertising	1	2.251
Industrial Marketing Management	2	1.663
Journal of Business Research	1	1.260
Applied Marketing Analytics	1	N/A
In total	45	

Table 1. Marketing journals, number of articles reviewed and Scimago journal rankings.

To structure my analysis, I have adapted the work of Wedel and Kannan (2016) as a base and divided the articles into seven focus areas: 1) Predicting sales and demand, 2) Segmentation and targeting, 3) Adaptive personalization, 4) Marketing insights, 5) Customer experience, 6) Marketing ROI, and 7) General implications. The number of articles in each area are listed in table 2. The review consists of 45 academic articles in total.

Each topic area will be discussed in three parts. First, I will give a quick overview of the topic at hand, and the machine learning techniques and applications available for business use today. Next, I will review the marketing literature on this phenomenon. Finally, I will include current calls for research from the Marketing Science Institute, as well as articles that review or discuss AI and machine learning in marketing (specifically Kumar 2018; Chui et al. 2018; Syan & Sharma 2018; Wedel & Kannan 2016; Balducci & Marinova 2018; Chung et al. 2016). The avenues for future research will be collated in section 4.

Focus Area	**# of Articles**
Predicting Sales and Demand	3
Segmentation and Targeting	3
Adaptive Personalization	2
Marketing Insights	22
Customer Experience	3
Marketing ROI	5
General Implications	7
In Total	45

Table 2. Number of articles reviewed in each focus area.

Study	Journal	Context & Findings	Topic Area	ML Methods	Citations
Ghose et al. (2012)	Marketing Science	Propose a new hotel ranking system. Mine product features from reviews using part-of-speech tagging and a clustering algorithm. The system outperforms benchmark systems.	Customer Experience	POS, clustering (Archak et al. 2011)	417
Netzer et al. (2012)	Marketing Science	Propose a method to mine UGC for market structures and marketing insights using conditional random fields.	Marketing insights	CRF (Lafferty et al. 2001)	381
Tirunillai & Tellis (2012)	Marketing Science	Find that the volume of UGC has a positive effect on stock performance, negative UGC has a negative effect, positive UGC does not have much influence.	Marketing ROI	Naive Bayes, SVM	375
Tirunillai & Tellis (2014)	Journal of Marketing Research	Propose a framework to dynamically map brand positions from user-generated-content (UGC), specifically satisfaction about brand quality.	Marketing insights	LDA	233
Teixeira et al. (2012)	Journal of Marketing Research	Emotion trajectories for the design of ads that leverage emotion and attention, with a facial expression classifying algorithm. The study shows that the level of surprise and the velocity of joy affect viewer retention the most.	Marketing insights	Algorithm from Nicu Sebe (University of Trento)	201
Rust & Huang (2014)	Marketing Science	Consider the implications of machine learning in service	Adaptive personalization	N/A	174
Wedel & Kannan (2016)	Journal of Marketing	Critically examine machine learning methods and give recommendations on marketing education.	General implications	N/A	153
Tang et al. (2014)	Journal of Marketing	Sentiment analysis of 600,000 Facebook and Youtube comments shows that neutral UGC affects sales depending on the type of UGC.	Marketing ROI	Sentiment Analysis	113
Homburg et al. (2015)	Journal of Marketing Research	Sentiment analysis from 115,000 posts shows that a firm's participation in online conversation has diminishing returns and can undermine consumer sentiment.	Marketing insights	SVM	85
Borah & Tellis (2016)	Journal of Marketing Research	Find that negative online chatter about a car brand increases negative chatter about other models and competing brands. The negative effect of a recall on sales is amplified by a factor of 4.5 by online chatter. Apology advertising has a negative effect for both recalled brand and rivals.	Marketing insights	3rd party classification algorithm	69

Table 3. Overview of the most influencial articles reviewed in the study, based on Google Scholar rankings.

3.1 Predicting Sales and Demand

Accurate predictions of demand and customer choice are important in many marketing applications (Jacobs et al. 2016). Unfortunately, many of the current statistical forecasting models and methods used in marketing research cannot handle large amounts of data well (Wedel & Kannan 2016). There are many choice prediction models in marketing (e.g. McFadden 1986; Fader and Hardie 1996), however the large amount of choices in online retail make the application of these models difficult (Naik et al. 2008). Machine learning has the potential to be of great use in this area, since it is well suited for big data (Chintagunta et al. 2016).

In marketing practice, examples of using machine learning methods for forecasting include estimating product-price elasticities, optimizing price points, predicting customer churn, conversion, product demand and inventory levels, as well as understanding product-sales drivers such as competitor prices, distribution and advertising (Chui et al. 2018). Machine learning has the potential to allow businesses to create better forecasts for their supply chain, develop better offerings, reduce waste and anticipate sales trends. In retail, machine learning is reported to reduce the error rate of forecasting by 30 to 50 percent compared to traditional methods (Bughin et al. 2017).

There are three articles in this review that address the topic of prediction using machine learning. Jacobs et al. (2016) use latent Dirichlet allocation (LDA) and mixtures of Dirichlet-Multinomials (MDM) models to predict what customers will purchase next, concentrating especially on large online retailers. Their machine learning approach outperforms other methods. Liu et al. (2016) demonstrate how content from social media platforms can be used for forecasting using machine learning and text mining. Their research spans two billion Twitter messages and 400 billion Wikipedia pages, and shows that the content and timeliness of tweets improves demand forecasting accuracy for TV shows. Most recently, Dzyabura et al. (2019) use machine learning to show that there is a large difference in how customers evaluate products online and offline, which might lead to suboptimal decisions when market research is done purely online. Their method improves predictions of up to 25% on individual choices, and up to 33% on market shares.

Based on the research, AI algorithms seem to provide a marked improvement over traditional forecasting methods. Despite the promising results, marketing literature in the field of forecasting using machine learning appears to be limited. Accordingly, there are many calls for research in this area. In his editorial in the Journal of Marketing, Kumar (2018) proposes future research on improving forecasting by combining machine learning and predictive analytics. Syan and Sharma (2018) extend this to enhancing forecasting in turbulent market conditions, as well as estimating demand on the basis of customer sentiment analysis. Based on the report by McKinsey Global Institute (Chui et al. 2018), venues for future research include forecasting demand, supply chains and inventory levels using machine learning.

3.2 Segmentation and Targeting

Segmentation and targeted marketing are the keys to market share growth in traditional marketing theory. There are many academic articles and marketing textbooks arguing for differentiation based on segmentation (e.g. Kotler & Keller 2016; McDonald and Dunbar 2004), making it a concept of central importance. On the other hand, empirical evidence on successful segmentation and targeting is rare (East et al. 2006), and widely tested models such as the NBD-Dirichlet (Goodhardt et al. 1984) give rise to the argument that markets are mostly unsegmented (Ehrenberg et al. 1997; Kennedy & Ehrenberg 2001a; Kennedy & Ehrenberg 2001b). In either case, there has been a lot of focus on segmentation driven by digital marketing and marketing analytics (Wedel & Kannan 2016), and machine learning promises powerful tools for it.

In marketing practice, machine learning algorithms are used to microsegment customers, group customers based on social media keywords and segment customers into groups inferred from the data, in order to target marketing activities or prevent churn (Chui et al. 2018). Both supervised and unsupervised learning are used. Segmenting can be distinct, such as demographics, or less distinct, such as product preferences. Deep learning algorithms are used to understand brand perceptions or discover joint marketing opportunities (Chui et al. 2018).

This topic area is addressed by a few articles in recent literature. Trusov et al. (2016) profile users with a proprietary algorithm and demonstrate its power by extracting behavioral patterns and recovering user profiles using the web surfing data of a large panel of people. Vidden et al. (2016) aim to provide better tools for segmentation. They compare machine learning clustering methods for market segmentation and find that latent class analysis (LCA) performs generally better than the other popular approaches, such as k-means clustering. By combining a random forest algorithm with field experiments, Ascarza (2018) shows that targeting customers identified as having the highest risk of churning is not an effective strategy and can actually increase churn. She argues that these programs should target based on sensitivity to the intervention, which does not correlate with a high risk of churning. This method improved retention in high-sensitivity groups up to 8.7 percentage points. While not assigned to this topic area specifically, Ansari et al. (2018) developed at supervised machine learning topic model for recommender systems, which can be used to target recommendations.

Despite being of central importance in traditional marketing strategy (e.g. Mcdonald & Dunbar 2004) and machine-learning-powered segmentation being used in marketing practice (Chui et al. 2018), in marketing academia segmentation using machine learning appears to be an understudied area. Syan and Sharma (2018) call for research in using machine learning for smart and continuous real-time targeting, and customer segmentation using both unsupervised and supervised learning.

3.3 Adaptive Personalization

Personalization means that the product, communications and other marketing-mix elements of the brand are tailored to the needs of the individual customer (Khan et al. 2009). Recent research supports personalized marketing, showing higher customer satisfaction, click-through-rates and positive effects on customer behavior (Ghose et al. 2014; Ansari & Mela 2003; Yao & Mela 2011; Khan et al. 2009). Another stream of work says that even though it does improve firm profits, personalization does not have a universal effect and has privacy concerns (Zhang & Wedel 2009; Goldfarb & Tucker 2011). Indeed, the Marketing Science Institute is calling for more research into whether personalization matters at all, and if yes, when (MSI 2018). Wedel & Kannan (2016) suggest that if used, personalization should not be automatically taken to the most granular level, even with individual data and tools such as machine learning. The optimal level should be chosen based on economies of scale and marketing ROI.

As a result of the recent advances in capturing customer heterogeneity, significant progess in this area has been made. Machine learning algorithms are used by companies to personalize products and services at the average, segment and individual consumer level (Wedel & Kannan 2016). State-of-the-art approaches include personalization of the marketing mix in mobile devices, receptivity of recommendations and adaptive personalization, resulting in marketing that automatically adapts to consumers' changing preferences at the individual level. Tech industry leaders such as Amazon and Google invest large sums of money in personalizing their marketing with machine learning (Bughin et al. 2017). Examples include Amazon's recommendations based on what else other customers bought and Apple iTunes' Genius (Jacobs et al. 2016).

In recent marketing literature, this was the least studied area, with only two papers directly investigating the phenomenon. While researching the implications of machine learning in service, Rust and Huang (2014) discuss personalization in relation to customer lifetime value (CLV) and find that heterogeneous consumer demand paired with a low estimated CLV should result in high amount of personalization on a transaction basis, and heterogeneous consumer demand paired with a high CLV should result in an adaptive personalization strategy. Chung et al. (2016) examine whether automated and adaptive personalization systems produce better products than self-customization, and find the results promising. In addition to these two papers, the research on recommender systems (e.g. Ansari et al. 2018) can also be used for personalization.

As evidenced by the lack of articles, there is a need for research in this topic area. The Marketing Science Institute (2018) is calling for research into how and when firms should personalize their customer experience for mass brands. Wedel and Kannan (2016) call research on what content should be personalized using machine learning and at what level, and how individual insights can be derived from large amounts of data. Also, the psychology of how customers react to adaptive personalization should be explored more (Chung et al. 2016), although at least some research exists indicating that personalization has both positive and negative consequences (Aguirre et al. 2016).

3.4 Marketing Insights

Customer insights and consumer research are at the heart of a firm’s consumer-based strategy and enable the firm to develop the right products at the right price, as well as communicate effectively with its customers (Hamilton 2016). Creation of a consumer-based strategy requires understanding customers and their wants and needs (Lam et al. 2013). Traditional research into customer insights includes surveys (Brocato et al. 2015), publicly available observational data (Thompson et al. 2015), experiments (Xie et al. 2015) and data on purchases (Carter & Curry 2013). However, these methods work for relatively small datasets. Current online platforms include billions of pieces of information in the form of text, images and videos, and machine learning has the ability to provide a means to structure and make sense of this huge amount of data (Hanssens & Pauwels 2016; Chintagunta et al. 2016).

In marketing practice, deep learning algorithms are used to conduct sentiment analysis to assess brand perception in the market, and to discover needs and preferences by collecting behavioral data from individual customers (Chui et al. 2018; Huang & Rust 2017). Machine learning is used for example to select the features that make a product most likely to be bought, predict how likely users are to click on an online ad, and provide insights on feelings engendered by stories, music and images (Chui et al. 2018a, 2018b).

In marketing research, mining and analyzing online user-generated content (UGC) has become the most popular application of machine learning in the last few years. Almost half of the 45 reviewed articles concentrate on gaining marketing insights from large amounts of online data using unsupervised machine learning, usually the latent Dirichlet allocation (LDA) topic model (see Blei et al. 2003) or support vector machines (SVM). Often, the data is comprised of hundreds of thousands, millions or even billions of reviews, comments or tweets.

Based on this review, there exists a healthy and growing body of research on gaining insights from big data using machine learning, and it appears the methodogy is becoming mainstream. This seems to be the only topic area that is not understudied, and calls for further research are additions to researchers' previous work, such as imploring future studies to find out the extent to which marketing actions are able to have an impact on customers' mental representations of brand personality (Chen et al. 2015) or gaining insights from product unboxing videos during product launches (Balducci & Marinova 2018).

3.4.1 Attitudes, Opinions and Sentiment

Gaining insights from online chatter is a popular topic. Homburg et al. (2015) conduct a consumer sentiment analysis using an SVM algorithm from 115,000 posts gathered from online forums and conclude that participation in online conversation shows diminishing returns for firms and can undermine consumer sentiment. Tirunillai and Tellis (2017) analyze how TV advertising affects online chatter. They use sentiment classification to label online reviews as positive or negative, using SVM and Naive Bayesian classification algorithms and show that TV advertising has a short but significant effect on positive online chatter, especially regarding visibility and virality. It has only a small short-term effect in reducing negative chatter. Culotta and Cutler (2016) devise a method to mine the data from a brand's Twitter account followers to acquire brand perception ratings.

Ordenes et al. (2018) compare a brand’s message intentions to brand message sharing by consumers using sentiment analysis with a support vector machine (SVM) algorithm. A two-year study of facebook posts and tweets by large consumer brands shows that customers prefer to share content that is informational or emotional, instead of calls to action. The most engagement was achieved by alliteration and images containing action combined with information or emotion, as well as varied cross-message compositions.

Borah and Tellis (2016) use data mined from around 1,000 online sites and classified with a proprietary third-party algorithm to research the effect of negative online chatter. They find that negative online chatter about a car brand increases negative chatter about other models and competing brands as well. A 1% increase in negative chatter decreased monthly sales by 4.3%, costing the brand $8.6 million, but also decreasing sales of its closest rival by 1.9%. However, the sales of the nearest competitor from another country increased by 2.2%. The negative effect of a recall on sales is amplified by a factor of 4.5 by online chatter. The research also shows that apology advertising has a negative effect for both recalled brand and rivals.

Liu et al. (2017) transform big data into brand insights through sentiment analysis. The researchers create a framework that finds latent brand topics and brand sentiments using deep learning and the LDA model. They use it on 1,7 million tweets from 20 different brands in five industries and show that customer emotions are often displayed in tweets about brands. Nam et al. (2017) harvest brand information by applying unsupervised machine learning methods to analyze user-spesified keywords in UGC using the LDA topic model. Tirunillai and Tellis (2014) propose a machine-learning-based framework to dynamically map brand positions from UGC, specifically satisfaction of brand quality.

There are several studies on online customer reviews. Büschken and Allenby (2016) propose a new model for text analysis based on sentence structure in reviews, extending the LDA algorithm. This ”bag-of-sentences” approach is found to provide more coherent results compared to the traditional ”bag-of-words” method. Felbermayr and Nanopoulos (2016) use a machine learning algorithm to identify the impact of emotion content in online reviews for predicting their helpfulness rating, which is influential in a buying decision. Based on their study, trust, joy and anticipation are the most important emotions.

3.4.2 Preferences and Needs

Identifying customer needs and preferences is a frequent topic in the reviewed papers. Chen et al. (2017) propose an approach for modelling consumers' preferences using sparse machine learning in conjoint analysis and show that their method is superior to traditional models. Timoshenko and Hauser (2019) use machine learning to screen UGC for qualitative analysis, in order to identify customer needs for product development and marketing strategy. Their research shows that the machine-learning approach is at least as effective in identifying customer needs as interviews and focus groups, and that the method is more cost-efficient. Liu and Toubia (2018) extend the LDA topic model for situations where two documents are semantically linked, such as online search queries and results. The resulting model can be used to infer customer preferences from search queries.

Netzer et al. (2012) mine and analyze UGC to create dynamic market structures and marketing insights using a conditional random field method (Lafferty et al. 2001). As an empirical application, the researchers mined 900,000 messages from a sedan car discussion forum and used a supervised machine learning algorithm to extract information. One of their findings was that Honda Accord was compared against other cars the most, and that it was compared against each of the 168 other cars at least once. The market structure created through machine learning was found to have a high correlation to the market structure created by traditional means. Huang and Luo (2016) propose an adaptational framework for understanding customer preferences for complex products. Their machine learning method works well for 70-100 attribute levels, which is traditionally considered unattainable for preference elicitation.

3.4.3 Customer Behavior

Zhang et al. (2017) examine how social media content and content-user fit influences sharing. Using LDA, the researchers provide insights on viral seeding strategies and how to tailor content for the preferences of different audiences in order to achieve rebroadcasts. Ursu (2018) examines the causal effect machine learning algorithms used for ranking by internet intermediaries have on customer behavior, and show that rankings lower search costs, and do not affect expectations or utility. Marchand et al. (2017) create a framework for consumer reviews and microblogs using the

SVM algorithm. The researchers test the framework on video game sales using 13 million tweets and 17,000 Amazon consumer reviews, and conclude that prior to launch, reviews, microblogs and advertising are the main drivers of sales. After launch microblogs quickly lose impact, but the impact of reviews grows. The valence of reviews is significant only at the end, microblogs never have much valence. Singh et al. (2017) create a machine learning model that predicts how useful an online review will be and automatically assigns a helpfullness rating to it.

Modern neuroscience, fMRI and eye tracking seem to go well in hand with AI. Chen et al. (2015) use machine learning techniques together with neuroimaging data to better understand brand associations. Their research shows that brand personality traits exists in the brain a priori, instead of being the cause of reflective thinking. Using brand personality and brain activity alone, the researchers were able predict the brand consumers were thinking about. Teixeira et al. (2012) develop emotion trajectories for the design of ads that leverage emotion and attention, with a facial expression classifying algorithm. The study shows that the level of surprise and the velocity of joy affect viewer retention the most. In contrast to this, Xiao and Ding (2014) analyze the faces of models in ads using a regression tree supervised machine learning algorithm, to test how models’ faces affect consumer attitudes and purchase intention. The empirical study shows that faces have a substantial and relatively consistent effect on these metrics, and that different faces are preferred by different segments.

3.5 Customer Experience

Customer experience is defined in marketing literature as the cognitive, affective and behavioral responses of customers towards a brand, through interacting with its various touchpoints, before, during and after purchase (Verhoef et al. 2009). Touchpoints include all contact with the brand, such as advertising and product usage. Customer experiences do not require a previous connection with the brand or a motivational state (Brakus et al. 2009). Customer experience has been deemed by practitioners to be among the most important concepts in marketing at the moment (Homburg et al. 2017). A study by Gartner (2014) shows that by 2016, 89% of companies in consumer industries expected to compete mainly with customer experience, thus making it an important consideration for machine learning applications.

In current marketing practice, machine learning is used for enhancing customer experience mainly through recommender systems, with companies such as Amazon, New York Times and Netflix making wide use of such systems (Ansari et al. 2018; Jacobs et al. 2016). Recommendations are based on the preferences of other customers with the same attributes or based on what the customer has bought before. Recurrent neural networks are also used to power chatbots that have the possibility to address nuanced customer inquiries and needs (Chui et al. 2018). The next steps for a positive customer experience might come via centralized machine learning analytics engines (Morgan 2017). In the future, emotional analytics might also enhance customer experience and engagement (Huang & Rust 2018).

I was able to find three academic articles on this topic, all studying recommender systems. In their highly cited work, Ghose et al. (2012) propose a hotel ranking system based on the utility gain of customers with heterogenous preferences. The researchers infer the economic impact of hotel characteristics, such as location and services, using a merged data set of hotel reservations, reviews, customer opinions, geotags, image classification and satellite images. Part-of-speech tagging and an unsupervised clustering algorithm (Archak et al. 2011) are used to mine product features from the reviews. The research finds that textual features have much more predictive power than numeric data. The system outperforms benchmark systems and is strongly preferred by users.

Lu et al. (2016) create a garment recommendation system that uses real-time videos, combining computer vision and machine learning algorithms to create an automated system that recognizes customers' preferences and makes personal recommendations. The system consistently outperforms two state-of-the-art non-automated systems, self-explicated conjoint and self-evaluation after try-on. Ansari et al. (2018) extend the supervised LDA topic model (Blei & McAuliffe 2010) for recommender systems. Their system creates rich characterizations of products and predicts customer preferences, based on user-generated reviews and product covariates. The system makes better recommendations than the benchmark model and addresses challenges of scalability. The work of Jacobs et al. (2016) on predicting customer purchases can be used in recommendation engines as well.

The academic literature for improving customer experience using machine learning is sorely lacking compared to interest in the practitioner domain. The Marketing Science Institute (MSI 2018) is currently calling for significant research in the area, including how to use machine learning for better customer engagement, how to recognize users anonymously, the role and functionality of human/tech interfaces (such as chatbots and virtual assistants), and capturing video, voice and text to improve customer experience. Syan and Sharma (2018) are asking for research on better recommendation systems for cross-selling and upselling.

3.6 Marketing ROI

Profit maximization and optimizing return on investment (ROI) have a long history in marketing science (Wedel & Kannan 2016), from optimizing advertising spend (Parsons & Bass 1971) to allocation of the company sales force (Mantrala et al. 1994) and targeted marketing (Bult & Wansbeek 1995). In recent years, Chief Marketing Officers have been under more and more pressure to prove the financial value of marketing to the firm (Farris et al. 2015; Hanssens &

Pauwels 2016). In light of this, it is no wonder a number of articles dealing with machine learning concentrate on marketing ROI, sales optimization and shareholder value.

In promising automated campaign research, Schwartz et al. (2017) demonstrate how a firm can adapt the immediate results of an online ad campaign to their benefit. Their adaptive multi-armed bandit field experiment with a retail bank delivered 750 million ad impressions and achieved a 8% improvement in acquisition compared to control campaign in two months. Tirunillai and Tellis (2012) use Naive Bayes and SVM algorithms to analyze the relationship between user-generated content (UGC) and stock market performance. The study finds that the volume of UGC has a positive effect and negative UGC has a negative effect on stock performance, but positive UGC does not have much influence. Offline advertising increases the volume of chatter and reduces negative UGC. Colicev et al. (2018) analyze data for 45 brands using the naïve Bayes classifier algorithm and show that a brand’s fan following leads higher brand awareness, improved purchase intent and higher customer satisfaction, and the latter two increase shareholder value. According to their research, earned social media valence has the largest effect on customer satisfaction. Owned social media affects purchase intent only for utilitarian brands and for brands with high reputation.

Tang et al. (2014) show that neutral UGC does not have a neutral effect on sales. Sentiment analysis of nearly 600,000 Facebook and Youtube comments shows that neutral UGC affects sales depending on the type of UGC (mixed-neutral or indefferent-neutral) and the distribution of positive and negative UGC. Hollenbeck (2018) analyzes how the value of branding is changing in response to online reputation mechanisms, using an unsupervised machine learning algorithm. The study finds that as the amount of information increases, the effect of brand names as signals of quality decreases. This is shown empirically through the over 50% decrease of the revenue of brand-name hotels from 2000 to 2015.

The Marketing Science Institute (MSI 2018) is currently calling for research in optimizing marketing spend to the individual exposure level, as well as measuring customer equity and ROI more effectively using novel approaches and data. Wedel and Kannan (2016) would like to see research identifying the financial impact of online and offline marketing. Based on the report by McKinsey Global Institute (Chui et al. 2018), future research should also be conducted on machine learning approaches to optimizing pricing.

3.7 General Implications

In addition to specific areas, there is a growing body of marketing literature addressing the broader impact of machine learning on marketing practice, research and policies. In reviewed literature, Rust and Huang (2014) consider the implications of machine learning in service, discussing personalization and standardization in relation to customer lifetime value (CLV). Wedel and Kannan (2016) critically examine some machine learning applications and give recommendations on developing marketing education. According to the researchers, marketing analysts of the future will increasingly need skills in statistics, econometrics, as well as machine learning techniques. In his editorial of the July 2018 issue of Journal of Marketing, Kumar (2018) discusses implications and applications of AI and machine learning on marketing practice. According to him, machine learning methods used in for example data security, natural language processing, personalization and recommender systems serve as a force for change in marketing research and practice.

Some of the reviewed articles address methods and techniques that could make the life of marketers easier. For example, Schwartz et al. (2014) aim to save the time of analysts by providing classification techniques from machine learning to recommend which model to use. For creative marketers, Toubia and Netzer (2017) develop a framework to automatically identify promising ideas by building semantic networks that balance novelty and familiarity, using supervised machine learning. The system also recommends words to the user to improve their idea.

There are many calls for general research in the application of machine learning in marketing. The Marketing Science Institute (MSI 2018) is asking for research on the best practices in machine learning for marketing, deploying AI, developing AI-related marketing skills, developing automated/programmatic campaigns and scaling A/B testing. Wedel and Kannan (2016) are calling for future research in combining machine learning with econometrics and theory-based methods, interpreting unstructured data and combining creativity and predicive and prescriptive machine learning methods.

4. Discussion and Implications

In this thesis I have reviewed recent marketing journal articles from leading publications addressing the application of machine learning in marketing. My research problem was to find the major research gaps regarding machine learning in current marketing literature and provide avenues for further research. In this process I have synthesized calls for research from the Marketing Science Institute (2018), as well as relevant articles pertaining to machine learning methods currently available. Table 4 summarizes these future research priorities. My research questions were:

1) To what extent are machine learning techniques addressed in research published in top marketing journals in 2012-2019?

I found 45 articles relating to machine learning in top marketing journals for this time period. 22 of these were in Marketing Science. Considering that machine learning is at its base a collection of methodological techniques, the number of articles is relatively high, which speaks to growing interest in these methods. Consequently, a major finding of this review is that machine learning is becoming a mainstream technology in marketing for both practitioners and academia. It is increasingly commonplace for marketing researchers to use machine learning to structure and make sense of data mined from large amounts of online data, such as reviews, tweets, tags and other user-generated content.

Machine learning is mostly used to glean marketing insights with sentiment analysis using algorithms such as support vector machines (SVM), or the latent Dirichlet allocation (LDA) topic model. Both of these have been designed specifically to handle big data (Liu et al. 2017). It is also worth mentioning that gaining insights from online chatter has been the main interest of many researchers in this review, with half of the studies dealing with online UGC in some way.

2) According to published papers and calls for research, what application areas of machine learning are understudied in marketing literature at the moment?

According to Palmatier et al. (2018), it is imperative that systematic reviews lay out directions for future research. To address this research question, I have compiled future directions for research in table 4. Many practical applications of machine learning appear to be understudied, with the only exception of customer insights. The thin amount of research is accentuated by the fact that machine learning techniques are able to consistently outperform previous methods in marketing research and practice. Several of the studies reviewed state that their machine learning approach beats traditional methods (e.g. Ghose et al. 2012; Chen et al. 2017; Ansari et al. 2018; Büschken & Allenby 2016; Huang & Luo 2016; Lu et al. 2016; Timoshenko & Hauser 2019). According to Wedel & Kannan (2016), this lack of research might be because researchers are reluctant to address machine learning techniques since they do not demonstrate causality or produce theoretical insights.

Machine learning algorithms provide a significant improvement for example in forecasting sales and demand (e.g. Jacobs et al. 2016; Liu et al. 2016), but there is very little research. Similarly, while segmentation is an integral part of marketing and machine learning offers powerful tools for it (Chui et al. 2018), segmentation using machine learning has barely been touched in academic research as of yet. The same can be said of adaptive and scalable personalization, which has garnered wide interest and significant advances (Wedel & Kannan 2016) but very little research. In customer eperience, the systems of Ghose et al. (2012) and Ansari et al. (2018) outperform benchmark systems, but the area has a marked lack of research. Althogether, most application areas of machine learning in marketing are understudied, as evidenced by calls for research from the Marketing Science Institute (MSI 2018).

Focus area	**Avenues for Future Research**
Predicting sales and demand	• Business implications of improved forecasting through machine learning (ML) (Kumar 2018) • Forecasting consumer demand, supply chain and inventory levels with ML (Chui et al. 2018) • Understanding product-sales drivers better using ML (Chui et al. 2018) • Estimating demand from customer sentiment, and comparing this with traditional methods of forecasting (Syan & Sharma 2018) • Estimating demand in rapidly changing environments (Syan & Sharma 2018)
Segmentation and Targeting	• Using ML for real-time customer targeting (Syan & Sharma 2018) • Customer segmentation using unsupervised neural networks (Syan & Sharma 2018) • Customer segmentation using supervised neural networks and customer labeling (Syan & Sharma 2018)
Adaptive personalization	• Does personalization matter at all (MSI 2018) • Personalizing customer experience using ML (MSI 2018; Wedel & Kannan 2016) • The optimal level of personalization (Wedel & Kannan 2016) • Automatic tailoring of campaign content based on individual data (Wedel & Kannan 2016) • Gathering individual insights from big data using ML (Wedel & Kannan 2016)
Marketing insights	• Gaining insights from user generated content during product launches (Balducci & Marinova 2018)
Customer experience	• Better engagement and personalized customer experiences (MSI 2018) • Human/tech interfaces (chatbots, virtual assistants) (MSI 2018) • Capturing video, voice & text to enhance customer experience (MSI 2018) • Recognizing users anonymously (MSI 2018) • Better recommendation systems (Syan & Sharma 2018)
Marketing ROI	• Optimizing marketing spend to the exposure level (MSI 2018) • Optimizing pricing (Chui et al. 2018) • Measuring customer equity and ROI more effectively (MSI 2018) • Identifying how online and offline marketing affect financial outcomes (Wedel & Kannan 2016) • Estimating causal effects at high speed using ML and econometrics (Wedel & Kannan 2016)
General Implications	• Best practices in machine learning for marketing (MSI 2018) • Deploying AI in marketing (MSI 2018) • Developing marketing skills for using AI (MSI 2018) • Creating automated/programmatic campaigns (MSI 2018) • Scaling A/B testing (MSI 2018) • Interpreting unstructured marketing data (Wedel & Kannan 2016) • Combining creativity and machine learning (Wedel & Kannan 2016)

Table 4. Directions for future research in applying machine learning in marketing.

4.1 Theoretical Implications

This study extends existing marketing literature in important ways. Since machine learning is becoming a mainstream marketing technology and is widely available, it is important that marketing literature keeps up with the recent developments. According to Bem (1995), reviews such as this one are an important part of science by offering a state-of-the-art overview of an area of interest. An up-to-date review of machine learning-related research has been lacking in marketing literature, and this thesis fills that gap. There is a need for a large amount of research in many areas of this subject, and this study will help in providing future directions for research, wich is an important part of the role of review papers (Palmatier et al. 2018).

The section concerning marketing insights should especially be of interest to academia. As the use of machine learning grows more and more mainstream, it is important that researchers are familiar with the possibilities of machine learning for their own research. Machine learning methods for structuring and gaining insights from very large quantities of data seem to be gaining momentum in marketing research. Adding techniques such as support vector machines (SVM) and the latent Dirichlet allocation (LDA) topic model to their arsenal will enable researchers to tackle the challenge of big data and online user-generated content (Liu et al. 2017).

4.2 Managerial Implications

This thesis provides several managerial implications. With the help of this review, marketing practitioners are able to gain a comprehensive overview of the current state of machine learning knowledge in marketing and can apply some of the research findings to their own business. Many of the individual research papers in this review have relevance for marketing practice, and open new, big-data-based avenues for thought.

An important consideration is whether the buzz around machine learning is warranted. Machine learning certainly can automate repetitive tasks and handle big data (Chintagunta et al. 2016). But as is often the case, people most likely overestimate the impact of the technology in the short-term and underestimate it in the long-term (Ratcliffe 2016). Machine learning will probably not deliver a large profit impact to most companies in the near future, at least at the scale predicted in surveys (e.g. Olson & Levy 2018). That said, large tech companies, such as Amazon and Google, are certainly profiting from algorithms (Bughin et al. 2017), and machine learning can have a major impact also for smaller companies, depending on their field.

Many applications of machine learning improve results in a significant way. The promise of more accurate sales forecasts and choice prediction is one such area. Machine learning was able to improve predictions up to 33%, and the method devised by Dzyabura et al. (2019) to combine a small offline research with a large online research was very cost-effective, and something marketing practitioners can implement for their own use.

The power of machine learning in handling big data is another highly useful area for practitioners. The ability to gain insights form reviews, tweets, posts and other user-generated content, using for example topic models, is very much a reality for companies, and most research promises capabilities that improve traditional methods, as well as cost reductions (e.g. Chen et al. 2017; Timoshenko & Hauser 2019). Other research shows companies what they should and should not do online, such as the analysis by Homburg et al. (2015) on the dimishing returns of active participation in conversations by the firm, the viral seeding strategies of Zhang et al. (2017), or the negative effects of apology advertising by Borah & Tellis (2016).

On the flip side, some of the current focus areas machine learning is applied to are not necessarily backed by empirical evidence as being effective. The concepts of microsegmentation, real-time campaign management, churn prevention and online funnel optimization are popular and based on traditional marketing theory; however, growing empirical data challenges the long-term profitability of these strategies, instead suggesting marketers use a sophisticated mass marketing, brand-building and acquisition-centered approach (Riebe et al. 2014; Binet & Field 2016; Graham et al. 2012). Marketers should be wary of simply using a technological solution and should first understand the strategy and empirical evidence behind the concept. Machine learning has the ability to greatly enhance marketing efforts, but it also has the potential to cause damage to profits if used in the wrong way.

For public policy, this review offers insights into the teaching of machine learning methodology in business schools. As Wedel & Kannan have (2016) pointed out, future marketing professionals need machine learning skills in their toolbox. As the technology becomes more and more mainstream in research and in practice, it is important that the teaching of marketing remains at the forefront of progress.

5. Conclusion

According to Palmatier et al. (2018), the benefits of review papers are that they provide an overview of a domain of interest, offer insights on key problems and lay out future research directions. The aim of this thesis has been just that. I have reviewed 45 articles, mostly from top marketing journals, addressing machine learning from the years 2012 to 2019, with some interesting findings and implications for both academia and practitioners. I have also provided a synthesis of major research gaps in this area, offering avenues for future research.

There are three main findings in this paper. First, machine learning approaches are able to significantly outperform traditional methods in most cases. It seems apparent that machine learning should be applied to and experimented with in a wide array of business uses in the future. Second, the use of machine learning algorithms to structure big data for marketing insights has become mainstream in both marketing academia and practice. Almost half of the reviewed articles discussed this aspect of machine learning. Third, apart from marketing insights, machine learning is addressed relatively little in marketing literature. This is in contrast to its wide interest in practice and the possibilities it offers in improving marketing. There are several large research gaps, namely in the areas of using of machine learning in prediction, adaptive personalization, segmentation, customer experience and marketing ROI, all of which have been barely touched in academia, despite promising results.

In my personal view, the main contribution of machine learning in this field will be in providing empirical generalizations for evidence-based marketing. This is arguably the goal of all science, even in social sciences where people rarely expect to see law-like patterns (Ehrenberg 1993). As algorithms are combined with the huge amounts of empirical data available, many of marketing’s theories will be put to the test, and we will gain a large amount of objective information about patterns in how markets function and customers buy. This promise of evidence-based decision-making with machine learning is echoed in the article in Nature by Jordan and Mitchell (2015). Automation, A/B testing and reinforcement learning will likely allow us to implement empirical generalizations fairly quickly into practice once they are proven to be effective in real life. It is likely that this development will be mostly led by practitioners, since it seems academics tend to shy away from the general models and difficult-to-prove causality of machine learning (Wedel & Kannan 2016). However, I hope these methods can be integrated with marketing theory.

As for practical application, it seems clear we have barely scratched the surface. Algorithms are already able to create text from raw data and write automated news stories and business reports (Conick 2016). In some companies, machine learning has been deployed for optimizing pricing, product design and marketing-mix applications (Wedel & Kannan 2016). Marketing is in the midst of very interesting developments, and the possibilities that machine learning brings to the field look promising indeed. We are just beginning to tap into the power of machine learning in marketing, and there remains a lot to research and learn.

5.1 Limitations

This study has some important limitations. First, I have reviewed articles mostly from major marketing journals. There are likely many machine-learning-related articles outside these flagship journals, some of which have not been reviewed here. There are also many marketing-related machine learning articles in journals of other disciplines, such as computer science and information sciences. Second, it is not always easy to discern which journal articles deal with machine learning. The term might not be in the heading or keywords, and is not always mentioned in the whole article, although individual machine learning algorithms might be used and mentioned. Terms such as predictive analytics, data mining, text mining, cognitive computing, intelligent systems and intelligent agents are sometimes used instead of machine learning. As machine learning methods grow in popularity, more and more researchers are using machine learning algorithms to structure their data, and sometimes the only way to find this out is by reading through the methodology section of each study. Also, the data itself might be from a third party that uses machine learning to structure the data. Therefore, it is quite possible that there are other articles in the reviewed journals during the time period that deal with or use machine learning and have not been reviewed here.

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Appendix A. Summary of papers applying machine learning in marketing.

Study	Journal	Context & Findings	Focus area
Ansari, A., Li, Y. & Zhang, J. (2018)	Marketing Science	Extend the supervised LDA topic model for recommender systems. The system creates rich characterizations of products and predicts customer preferences, based on user-generated reviews and product covariates. The system makes better recommendations than the benchmark model with manual covariates, and addresses challenges of scalability.	Customer experience
Ascarza, E. (2018)	Journal of Marketing Research	Use a random forest algorithm and fields experiments in contractual markets to show that targeting customers with the highest risk of churning is not an effective strategy. Retention programs should target based on sensitivity to the intervention, which does not correlate with high risk of churning. The method improved retention up to 8.7 percentage points.	Segmentation and Targeting
Balducci, B. & Marinova, D. (2018)	Journal of the Academy of Marketing Science	Conceptualize unstructured data in marketing, review articles using machine learning (ML) for unstructured data and identify gaps in extant literature.	General implications
Borah, A., & Tellis, G. J. (2016)	Journal of Marketing Research	Use data mined from 1,000 online sites and classified with a 3rd party algorithm and find that negative online chatter about a car brand increases negative chatter about other models and competing brands. The negative effect of a recall on sales is amplified by a factor of 4.5 by online chatter. Apology advertising has a negative effect for both recalled brand and rivals.	Marketing insights
Büschken, J., & Allenby, G. M. (2016)	Marketing Science	Propose a new model for text analysis based on sentence structure in reviews, extending the Latent Dirichlet Allocation (LDA) topic model. This ”bag-of-sentences” approach is found to provide more coherent results compared to traditional ”bag-of-words” method.	Marketing insights

Chen, Y., Iyengar, R. & Iyengar, G. (2017)	Marketing Science	Propose an approach for modelling consumers' preferences using sparse ML in the context of conjoint analysis and show that their method is superior to traditional benchmark models.	Marketing insights
Chen, Y., Nelson, L. D. & Hsu, M. (2015)	Journal of Marketing Research	Use ML together with neuroimaging data to better understand brand associations inside the brain. Show that aspects of brand personality already exist in the brain instead of being the cause of reflective thinking. Were able to predict what brand people thought about based on brain activity and brand personality.	Marketing insights
Chung, T. S., Wedel, M. & Rust, R. (2016)	Journal of the Academy of Marketing Science	Look at whether automated and adaptive personalization systems produce better products than self-customization, and find the results promising.	Adaptive personalization
Colicev, A., Malshe, A., Pauwels, K. & O'Connor, P. (2018)	Journal of Marketing	Analyze data for 45 brands using the naïve Bayes classifier algorithm and show that having a following improves the awareness, purchase intention and satisfaction of brands, and the latter two increase shareholder value. Earned social media valence has the largest effect on customer satisfaction. Owned social media affects purchase intent only for utilitarian brands and for brands with high reputation.	Marketing ROI
Culotta, A. & Cutler, J. (2016)	Marketing Science	Develop a method to automatically mine the data from a brand's Twitter account followers to acquire brand perception ratings.	Marketing insights
Dzyabura, D., Jagabathula, S. & Muller, E. (2019)	Marketing Science	Use hierarchical Bayesian approach and k-nearest neighbor algorithm to calibrate the relationship of online and offline customer choice. Show that there is a large difference in how customers evaluate products online and offline, which might lead to suboptimal decisions when market research is done online. Their method improves predictions of up to 25% on individual choices, and up to 33% on market shares.	Predicting sales and demand
Felbermayr, J. & Nanopoulos, A. (2016)	Journal of Interactive Marketing	Use a random forests algorithm to examine the emotion content in online reviews for predicting their helpfulness rating, which is	Marketing insights

		influential in a buying decision. The study shows that trust, joy and anticipation have the most impact in decision-making.	
Ghose, A., Ipeirotis, P. G., & Li, B. (2012)	Marketing Science	Propose a hotel ranking system based on the utility gain of customers with heterogenous preferences. Infer the economic impact of hotel characteristics using a merged data of hotel reservations and UGC. Part-of-speech tagging and unsupervised clustering is used to mine product features from reviews. The system outperforms benchmark systems and is preferred by users.	Customer experience
Hollenbeck, B. (2018)	Journal of Marketing Research	Researches how the value of branding is changing in response to online reputation mechanisms, using an unsupervised ML algorithm. The study finds that as the amount of information increases, the effect of brand names as signals of quality decreases. This is shown empirically through the over 50% decrease of the revenue of brand-name chain hotels from 2000 to 2015.	Marketing ROI
Homburg, C., Ehm, L., & Artz, M. (2015)	Journal of Marketing Research	Conduct a consumer sentiment analysis using a SVM algorithm from 115,000 posts from ten online forums and conclude that active firm participation shows diminishing returns and can undermine consumer sentiment.	Marketing insights
Huang, D. & Luo, L. (2016)	Marketing Science	Propose an adaptational framework for understanding customer preferences for complex products, using fuzzy support vector machines. Their ML method works well for 70-100 attribute levels, which is traditionally considered unattainable for preference elicitation.	Marketing insights
Jacobs B. J. D., Donkers, B. & Fok, D. (2016)	Marketing Science	Use LDA and mixtures of Dirichlet-Multinomials (MDM) to predict what customers will purchase next, pertaining to large online retailers. The machine learning approach outperforms other methods. These advances can be used in personalization or recommendation engines.	Predicting sales and demand

Kumar, V. (2018)	Journal of Marketing	Discuss implications and applications of AI and ML on marketing practice and research, while proposing a definition and framework for transformative marketing.	General implications
Liu, J. & Toubia, O. (2018)	Marketing Science	Extend the LDA topic model for situations where two documents are semantically linked, such as search queries and results. The resulting model can be used to infer customer preferences from search queries.	Marketing insights
Liu, X., Burns, A. C., & Hou, Y. (2017)	Journal of Advertising	Use sentiment analysis for insights on brands. Create a framework to derive latent topics with deep learning algorithms and LDA. Analyze 1,7 million tweets and find that brand-related tweets usually have emotional content.	Marketing insights
Liu, X., Singh P. V., & Srinivasan K. (2016)	Marketing Science	Demonstrate how content from social media is used in forecasting using ML. The research spans two billion Twitter messages and 400 billion Wikipedia pages, and shows that the content and timeliness of tweets improves demand forecasting accuracy for TV shows.	Predicting sales and demand
Lu S., Xiao L. & Ding M. (2016)	Marketing Science	Propose a garment recommender system that uses real-time videos, combining computer vision and ML algorithms to create an automated system to recognize customers' preferences and make recommendations. The system consistently outperforms two state-of-the-art non-automated systems, self-expilcated conjoint and self-evaluation after try-on.	Customer experience
Marchand, A., Hennig-Thurau, T., & Wiertz, C. (2017)	International Journal of Research in Marketing	Create a framework for consumer reviews and microblogs using the SVM algorithm. The researchers test the framework on video game sales using 13 million tweets and 17,000 Amazon consumer reviews, and conclude that prior to launch, reviews, microblogs and advertising are the main drivers of sales. After launch microblogs quickly lose impact, but the impact of reviews grows. The valence of reviews is significant only at the end, microblogs never have much valence.	Marketing insights

Martínez-López, F. J. & Casillas, J. (2013)	Industrial Marketing Management	Provide a literature review of AI systems in marketing, concentrating on industrial marketing.	General implications
Nam, H., Joshi, Y. V. & Kannan, P. K. (2017)	Journal of Marketing	Harvest brand information by applying unsupervised machine learning methods to analyze user-spesified keywords in UGC using the LDA topic model.	Marketing insights
Netzer, O., Feldman, R., Goldenberg, J., & Moshe, F. (2012)	Marketing Science	Propose a method to mine and analyze UGC to generate dynamic market structures and marketing insights using a conditional random field. Demonstrate the method with cars and diabetes drugs.	Marketing insights
Ordenes, F. V., Grewal, D., Ludwig, S., de Ruyter, K., Mahr, D., & Wetzels, M. (2018)	Journal of Consumer Research	Compare a brand’s message intentions to brand message sharing by consumers using sentiment analysis with an SVM algorithm. A two-year study of facebook posts and tweets shows that brand messages containing emotional or information content are shared more often than calls to action. Alliteration and action images combined with informational or emotional messages results in more engagement, as will varied cross-message compositions.	Marketing insights
Rust, R. T. & Huang, M. H. (2014)	Marketing Science	Consider the implications of ML in service. Discuss personalization, standardization, relational approach and transactional approach in relation to CLV.	Adaptive personalization
Schwartz, E. M., Bradlow, E. T., & Fader, P. S. (2017)	Marketing Science	Demonstrate how a firm can adapt the immediate results of an online ad campaign to their benefit. The adaptive multi-armed bandit field experiment with a retail bank delivered 750 million impressions and achieved a 8% improvement in acquisition compared to control campaign in two months.	Marketing ROI
Schwartz, E. M., Bradlow, E. T. & Fader, P. S. (2014)	Marketing Science	Provide classification techniques from ML to recommend which model researchers should use.	General implications
Singh, J. P., Irani, S., Rana, N. P., Dwivedi, Y. K., Saumya, S., & Kumar Roy, P. (2017)	Journal of Business Research	Create a ML model that predicts how useful an online review will be and automatically assigns a helpfullness rating to it.	Marketing Insights

Syam, N. & Sharma, A. (2018)	Industrial Marketing Management	Discuss the impact of ML on sales practice in the industrial marketing sector and provide a research agenda.	General implications
Tang, T., Fang, E. & Feng, W. (2014)	Journal of Marketing	Finds that neutral user-generated content has a non-neutral effect on product sales. Sentiment analysis of nearly 600,000 Facebook and Youtube comments shows that neutral UGC affects sales depending on the type of UGC (mixed-neutral or indefferent-neutral) and the distribution of positive and negative UGC.	Marketing ROI
Teixeira, T., Wedel, M. & Pieters, R. (2012)	Journal of Marketing Research	Develop emotion trajectories for the design of ads that leverage emotion and attention, with a facial expression classifying algorithm. The study shows that the level of surprise and the velocity of joy affect viewer retention the most.	Marketing insights
Timoshenko, A. & Hauser, J. (2019)	Marketing Science	Propose a ML approach to UCG for qualitative analysis, in order to identify customer needs for product development and marketing strategy. Cluster data using a convolutional neural network. Show that the ML approach is at least as effective in identifying customer needs as interviews and focus groups, and more cost-efficient.	Marketing insights
Tirunillai, S. & Tellis, G. (2014)	Journal of Marketing Research	Propose a ML framework to dynamically map brand positions from user-generated-content, specifically satisfaction about brand quality.	Marketing insights
Tirunillai, S. & Tellis, G. (2017)	Marketing Science	Analyze how TV advertising affects online chatter. Use sentiment classification to classify online reviews as positive or negative, using SVM and Naive Bayesian classification algorithms. Show that TV advertising has a short but strong effect on positive online conversation, especially regarding visibility and virality. It has only a small short-term effect in reducing negative chatter.	Marketing insights
Tirunillai, S., & Tellis, G. J. (2012)	Marketing Science	Use Naive Bayes and SVM algorithms to analyze UGC and stock market performance. The study finds that the volume of UGC has a positive effect, negative UGC	Marketing ROI

		has a negative effect, and positive UGC does not have a significant effect. Offline advertising creates more chatter and less negative UGC.	
Toubia, O. & Netzer, O. (2017)	Marketing Science	Automatically identify promising ideas by building semantic networks balancing novelty and familiarity, using supervised ML. Test the effect with 4,000 ideas. The system also recommends words to the user to improve their idea.	General implications
Trusov, M., Ma, L. & Jamal, Z. (2016)	Marketing Science	Concentrate on user profiling with a proprietary algorithm and demonstrate its power by extracting behavioral patterns and recovering user profiles using the web surfing data of a large panel of people.	Segmentation and Targeting
Ursu, R. (2018)	Marketing Science	Examines the causal effect ML algorithms used for ranking by internet intermediaries have on customer behavior, and shows that rankings lower search costs, and do not affect expectations or utility.	Marketing insights
Vidden, C. et al (2016)	Applied Marketing Analytics	Compare ML clustering methods for market segmentation, and find that latent class analysis (LCA) performs generally better than the other approaches, such as KM.	Segmentation and Targeting
Wedel, M. & Kannan P. K. (2016)	Journal of Marketing	Critically examine ML methods and give recommendations on marketing education. According to the researchers, marketing analysts of the future will need skills in statistics, econometrics, computer science and marketing.	General implications
Xiao, L. & Ding, M. (2014)	Marketing Science	Analyze faces used in ads using a regression tree supervised ML algorithm, to test the effect of faces on purchase intention and attitudes regarding the ad and the brand. The empirical study shows that faces have a substantial and relatively consistent effect on these metrics, and that different faces are preferred by different segments.	Marketing insights
Zhang, Y., Moe, W. W., & Schweidel, D. A. (2017)	International Journal of Research in Marketing	Examine how sharing is affected by content and content-user fit using LDA. Provide insights about seeding strategies and tailoring content to achieve rebroadcasts.	Marketing insights